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Detection and Mapping of Slow-moving Landslides with Pleiades-1 Data

[1*]Eyo E., [2]Gbedu A., [2]Faruna S., [2]Bako M. & [1]Adewale O.
[1]Department of Surveying & Geoinformatics, Bells University of Technology, Ota
[2]Department of Surveying & Geoinformatics, Federal University of Technology, Minna
[*]Corresponding author: geoetim@gmail.com; etim.eyo@bellsuniversity.edu.ng

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The study utilised the k-NN and SVM algorithms, Pleiades-1 data, and object-based image analysis for the classification and mapping of slow-moving landslides in Kutlugün in Maçka district of Turkey. The approaches employed were based on the investigation of the influences of the training sample sizes and type (balanced/imbalanced) on the accuracy of the classification results. A total of 128 and 134 small landslides were detected using k-NN and SVM algorithms, respectively. The SVM method had higher producer accuracy (85.9%), user accuracy (89.4%) and kappa index (0.82) compared to the k-NN algorithm that had producer accuracy (83.1%), user accuracy (86.0%) and kappa index (0.80). Using the imbalanced datasets, the classification accuracy of SVM was not significantly different among the five different training sample sizes, with 83.75% for the lowest dataset (dat2) and 85.12% for the highest dataset (dat5). On the other hand, the classification accuracy of k-NN was significantly different between the smallest sample size (dat1, 79.80%) and the largest sample size (dat5, 84.59%). When balanced datasets were used, the SVM algorithm produced accuracy of 85.07% compared to k-NN classifier (84.10%), showing that there was no pronounced difference on the performance of the two classifiers on different training sample sizes. The overall evaluation of the two algorithms show that using supervised classification at object level with Pleiades-1 image, for slow-moving landslide detection and mapping, is possible and can be improved.
Keywords: Small landslides; Pleiades-1; k-Nearest Neighbour (k-NN); Support Vector Machine (SVM); Imbalanced datasets; Balanced datasets

Introduction

Landslides play a key role in the evolution of landscapes and represent a serious geological hazard, mostly in mountainous regions of the world (Novellino *et al*., 2024; Sassa *et al*., 2015). The expansion of urban settlements into mountainous terrains exposes people to the hazards and risks associated with landslides. Landslides have caused destruction to thousands of lives and damage to infrastructures and properties annually (Holbling *et al*., 2012). Mapping for landslide susceptibility and hazard assessment are important requirements for land-use planning. This is particularly useful to avoid expanding urban settlements into landslide-prone areas, thus mitigating future economic and human losses.

The main motivation of the study was based on the existence of slow-moving landslides in Kutlugün of Macka, Turkey. Slow-moving landslides have extremely slow and very slow (<1.6 m/year) displacement rates, according to the classification proposed by Cruden and Varnes (1996). Compared to fast-moving landslides, slow-moving landslides may not necessarily result to loss of lives, but they may be precursors for faster and destructive mass movements and can cause severe disruption to critical infrastructures such as roads and buildings (Fu et al. 2025; De Vries *et al*. 2024; Rana *et al*. 2026).

The availability of VHR optical satellite images (e.g. QuickBird, Pléiades-1, WorldView-1 and -2, and GeoEye-1 and -2) has made it possible to map landslides more accurately and effectively as more detailed information on landscape composition and dynamics can be derived (Guzzetti *et al*., 2012). Pléiades-1 is the satellite system of the French-Italian Optical and Radar Federated Earth Observation program designed for land and coastal applications. It includes Pleiades-1A which was launched in December 2011, and Pleiades-1B launched in December 2012. Pleiades-1A and 1B share the same orbital plane as SPOT-6 and 7 giving daily revisits over any point on the Earth.

The performances of k-NN and SVM classifiers and Pleiades-1 data for the detection and mapping of slow-moving landslides were evaluated in the study. The k-NN algorithm is a standard method, which has been employed by professionals in practice, while the SVM classifier is a modern technique for scientific studies. The approaches employed were based on the investigation of the influences of the training sample sizes and type (balanced/imbalanced) on the accuracy of the classification results. The results contributed to the increasing application of Pleiades-1 images in landslide studies.

Materials and Methods

Study area

The study area is about 25 km^2 located in Kutlugün in Maçka district of Turkey (Figure 1). The area experiences temperate climate in summers and rainy season usually starting from September and ending around April. The topography consists of hillsides, mountains, valleys and stream channels. The hydrology of this area is regulated by the activities of Değirmendere River Basin, which is surrounded by high mountains with maximum elevation of 3080 m. The geology of Kutlugün landslide area consists of weathered andesite-basalt and pyroclastic rocks, with clays developing due to the weathering of the rocks (Yalçinkaya & Bayrak, 2005). Road construction, quarrying and tunnelling through the high mountainous terrain are the main anthropogenic activities in the study area. The type of landslides movement in the study area is translational, and the movement amounts to several centimetres per month (Yalçinkaya & Bayrak 2005).

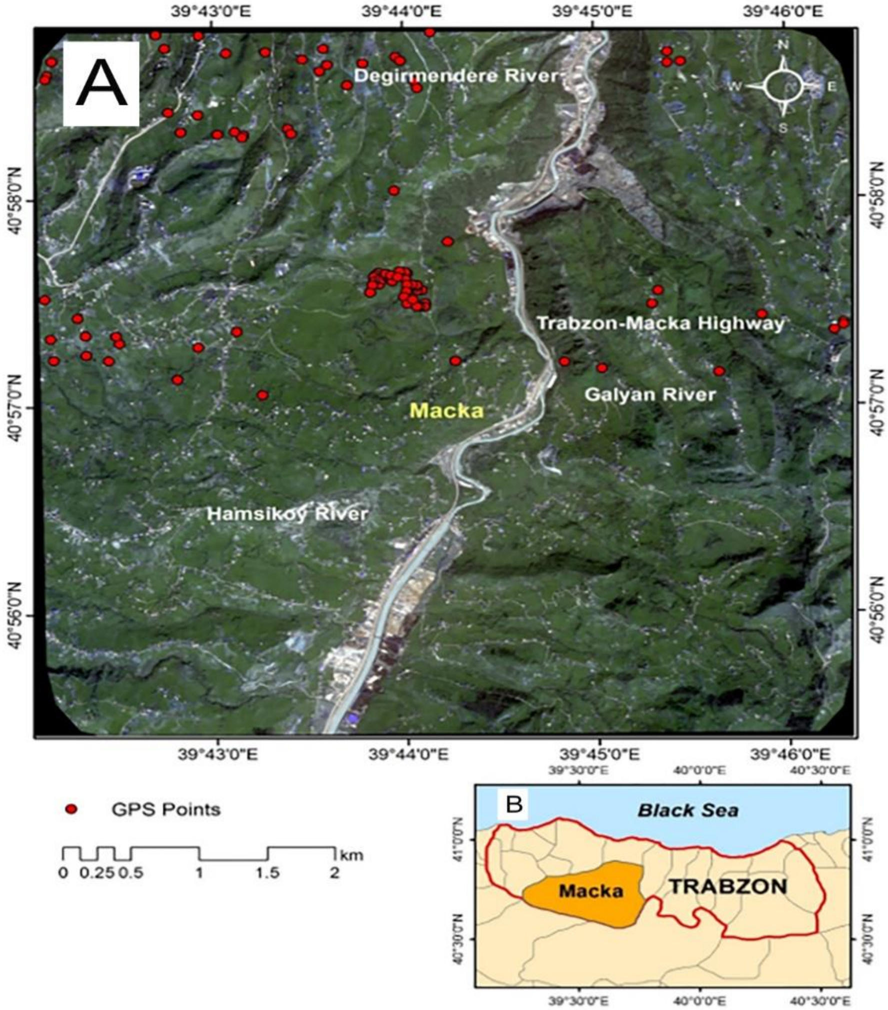

Figure 1: (A) Pleiades-1 image of study area showing GPS points; (B) Map of Turkey showing location of study area

Data and materials

The data employed for the study along with the acquisition parameters is given in Table 1.

Table 1: Data used for the study

Data	Data/time of acquisition (dd/mm/yyyy)	Mean Across/ Mean along track viewing angle	Mean Across/ Mean along track incidence angle	Solar azimuth/ elevation	Spectral bands	Resolution
Pleiades-1 (Mono)	21-10-2017 08:30:15.8	15.66/ -12.24	-19.79/ 9.97	168.92/ 37.70	PAN: 0.47-0.83 µm (black and white); MS bands: Blue = 0.43-0.55 µm; Green = 0.50-0.62 µm; Red = 0.59-0.71 µm; Near Infrared = 0.74-0.94 µm	PAN = 0.7 m MS = 2.8 m
Pleiades-1 (Mono)	03-04-2018 08:18:20.9	-4.47/ 2.08	5.26/ -1.20	152.73/ 51.66		
RTK-GPS 1	24-10-2017					5 mm
RTK-GPS 2	25-01-2018					
RTK-GPS 3	25-03-2018					
ASTER GDEM	17-10-2015					30 m

Methods

The workflow is based on the object-based supervised classification (or example based) technique with the following steps - data pre-processing, image segmentation, the selection of training and testing samples with emphasis on the effect of the training sample sizes (balanced and imbalanced datasets), detection of landslide objects and accuracy assessment. The performance of two classifiers: non-parametric k-Nearest Neighbours (k-NN) and Support Vector Machine (SVM) is evaluated using Pleiades imagery, to detect and map slow-moving landslides in the Kutlugün study area. The example based feature extraction approach is implemented in the ENVI 5.1 image processing software.

Data pre-processing

The Pleiades-1A image acquired on 3 April 2018 was used. Radiometric calibration and atmospheric correction were performed using ENVI to obtain the surface reflectance data of the acquired Pleiades-1 imagery. The georeferenced Pleiades-1 imagery was orthorectified using the ASTER GDEM. The high-spatial-resolution multispectral Pleiades-1 imagery was enhanced by combining 0.7 m resolution panchromatic and 2.8 m resolution multispectral data with the ENVI PCA Pan-Sharpening module. ASTER GDEM was also used to calculate the topographic parameters (slope and elevation) of landslides in the study area.

Image segmentation

The object-based image analysis (OBIA) approaches rely on good algorithms of segmentation. Image segmentation is a process which involves separating the image into objects or regions using the homogeneity of the pixel values. In the detection and mapping of slow-moving landslides, image segmentation is performed to create objects or segments that completely delineate the boundary of the landslide features. In this paper, the edge-based segmentation algorithm was implemented in ENVI 5.1 to extract slow-moving landslide features from the Pleiades-1 image.

Selection of training and testing samples

The key aspect of a classification system is that it should be able to accommodate numerous variables such as imagery type, classifications needed, feature importance, and training data quality. It is important in the classification process to not only consider the object of interest, which is landslide in this study, but also to classify as many surrounding objects as possible. This approach is useful in understanding the variations in spectral, textural and spatial values of surrounding objects.

In the Kutlugün study area, the main land use/cover are green tea, hazelnut, deciduous, coniferous, pasture, soil, rock, water, agriculture, and urban (Kavzoglu *et al*., 2015). In this study, training and sample data were generated from main four classes covering all the land cover, namely - landslide, road, building, and vegetation (Table 2).

Table 2: Training and testing samples for individual class

Land Cover	Training	Testing
Landslide	100	107
Road	100	161
Building	100	132
Vegetation	100	135

Class-imbalance and class-overlap are problems commonly encoutered in kernel-based classification using satellite imagery datasets, in view of the tendency to over-fit to the majority class so as to reduce total error (Mountrakis *et al*., 2011; He & Garcia, 2009). Landslides is generally a minority class compared to other surrounding objects in the landscape (Stumpf & Kerle, 2011). Thus, the classification of landslide objects is susceptible to imbalance. Therefore, selecting training samples of other surrounding objects using natural class balance will be favourable to the majority class and tend to under-fit to landslides, thereby contributing to excessive misses. One main solution proferred to this problem invlolves oversampling the minority class by applying synthetic samples to strengthen features space representation (He & Garcia, 2009).

In order to evaluate the performance of the two classification algorithms and the effect of the training sample sizes on the classification accuracies, five imbalanced and five balanced datasets were generated with the following sizes - 10%, 20%, 30%, 40%, and 50% of the total training data.

Classification algorithms

The two main classfication techniques applied in this study are the Supprt Vector Machine (SVM) and k-Nearest Neighbours (k-NN). Support Vector Machine (SVM) belong to a family of boundary classifiers which have been applied in remote sensing applications (Mountrakis et al., 2011). One main goal of SVM algorithm is to determine an optimal decision boundary (or hyperplane) and to segregate the dataset into a pre-defined number of classes (Vapnik, 1999). SVM seeks to determine the widest margin between two classes in feature space. In order to maximize the margin between the classes, SVM need to divide the classes with a decision surface. The surface is referred to as the optimal hyper-plane. The critical elements of the training set are the support vectors and they are the data points closest to the hyper-plane. The SVM approach involves different classes which are linearly separable and based on a non-linear transformation of the covariates. As is common with imagery datasets with inherent problem of class overlap, the assumption of linear separability becomes invalid. In order to produce higher order and non-linear solutions using SVM algorithms, the slack-variable kernels such as radial basis functions are introduced. SVM produces robust classification under class-imbalance and variable cross-correlation with the appropriate choice of features, kernels and parameters (Statnikov *et al*., 2008). SVM may be employed independently to variable selection, though the internal measures of variable importance are not included (Archibald & Fann, 2007). SVM algorithms have been extensively applied in landslide susceptibility mapping (Lee *et al*., 2017; Heleno *et al*., 2016; Ballabio & Sterlacchini, 2012), due to their capability to utilise data with unknown statistical distributions and small training samples.

The k-NN algorithm is a non-parametric technique which has been applied in statistical applications since the early 1970's (Franco-Lopez *et al*., 2001). Being a non-parametric method, no assumptions are required on the underlying data distribution. It is referred to as a lazy algorithm beacause it does not apply the training data points to perform any generalization. The principle of k-NN is based on the use of calibration dataset to find a group of k samples that are nearest to unknown samples (e.g., based on distance functions). The technique computes the Euclidean distance from each image segment to every defined training sample. The distance is measured in an n-dimensional space, where n represents the number of attributes for the individual training sample. The class of unknown samples are determined from these k samples by computing the average of the response variables (i.e., the class attributes of the k-NN) (Akbulut *et al*., 2017). The k is a tuning parameter, and plays an important role in the performance of the k-NN algorithm (Qian *et al*., 2015). k-NN classifier is very suitable for experimenting because it only requires one parameter (k) to be optimized. k-NN algorithms have been employed in landslide detection and mapping (Cheng *et al*., 2013; Li *et al*., 2013).

Supervised classification process and tuning parameter

When applying SVM and k-NN algorithms, the tuned parameters is important in obtaining high accuracy results. The tuning steps and tuned parameters are different for each classifier. In this paper, a series of values for the tuning process was tested for each classifier, with the aim of determining the optimal parameters to produce the highest overall classification accuracy. The best parameters applied to produce the classified results were employed to compare the performance of the classifiers. In ENVI 5.1 image processing software the parameter adopted for the k-NN classifier is - number of neighbors: 1.

The four types of kernels for SVM classifier in ENVI 5.1 are: linear, polynomial, radial basis function (RBF), and sigmoid. The RBF is the commonly used kernel and performs well in land cover classification studies (Shi & Yang, 2015). The best prediction accuracy was realised with the RBF kernel, and the following processing parameters were adopted after several tests - degree of kernel polynomial: 1, bias in kernel function: 1, gamma in kernel function: 0.03, penalty parameter: 100. In the processing scheme, 95% was set as the classification confidence threshold, implying that features with less than 95% confidences in each class were set to unclassified.

Accuracy assessment

Accuracy assessment was implemented in the study based on user accuracy (UA), producer accuracy (PA), and kappa index. The results of the supervised object-based classification were also compared with the landslide inventory map of the study area based on RTK-GPS field survey of 95 known points within the landslide study area.

Results and Discussion

Landslide detection using the two classifiers

Figure 2 shows the results of landslide mapping of the training and testing samples using k-NN and SVM models. These two algorithms are efficient and of high accuracy. The map shows the detected landslides in brown, road in purple, building in yellow and vegetation in green. A total of 128 small landslides were detected in the study area using k-NN algorithm (Figure 3), while a total of 134 landslides were detected using SVM algorithm (Figure 4). The SVM method had higher producer accuracy (85.9%), user accuracy (89.4%) and kappa index (0.82) compared to the k-NN algorithm that had producer accuracy (83.1%), user accuracy (86.0%) and kappa index (0.80).

The inventory map of the Kutlugün study area consists of coordinates of 95 points acquired using RTK-GPS periodic field observations. The accuracy of the detected landslides was realised by using ArcMap 10.3 to compare the observed GPS points with the polygons obtained from the semi-automated OBIA-derived landslides. The results of the point-to-polygon comparison are given in Figure 3 and 4. The accuracy using k-NN algorithm was 80.4%, while that of SVM algorithm was 83.75%.

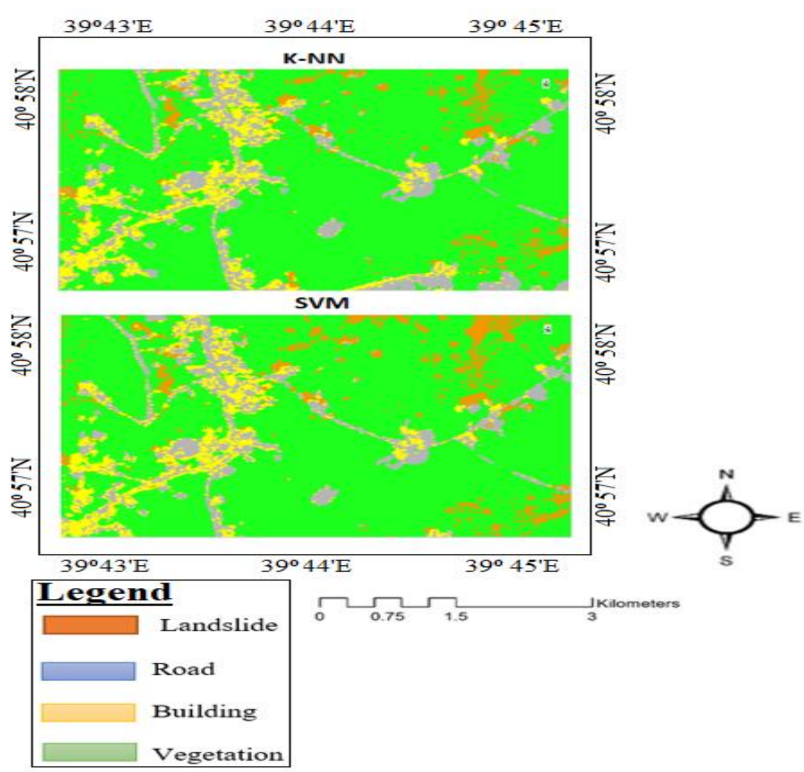

Figure 2: Training and testing samples for the separation of landslide from other surrounding objects

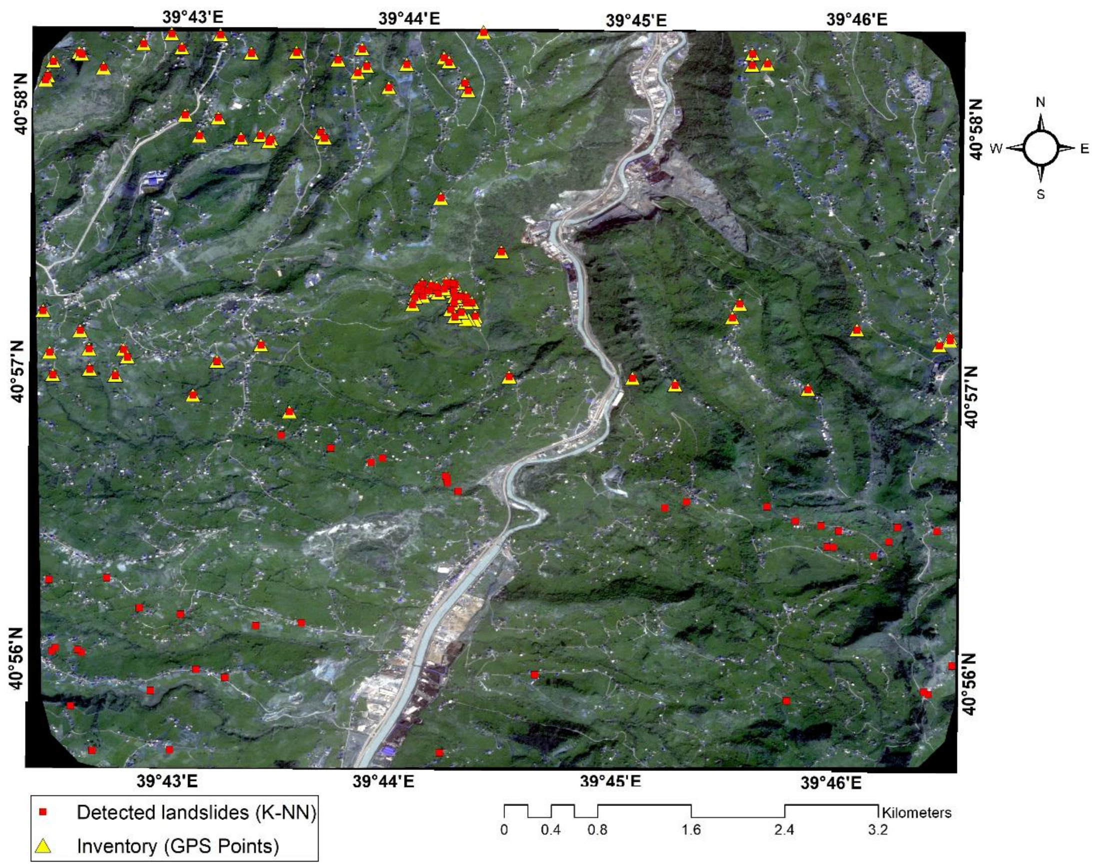

Figure 3: Detected landslides using k-NN algorithm

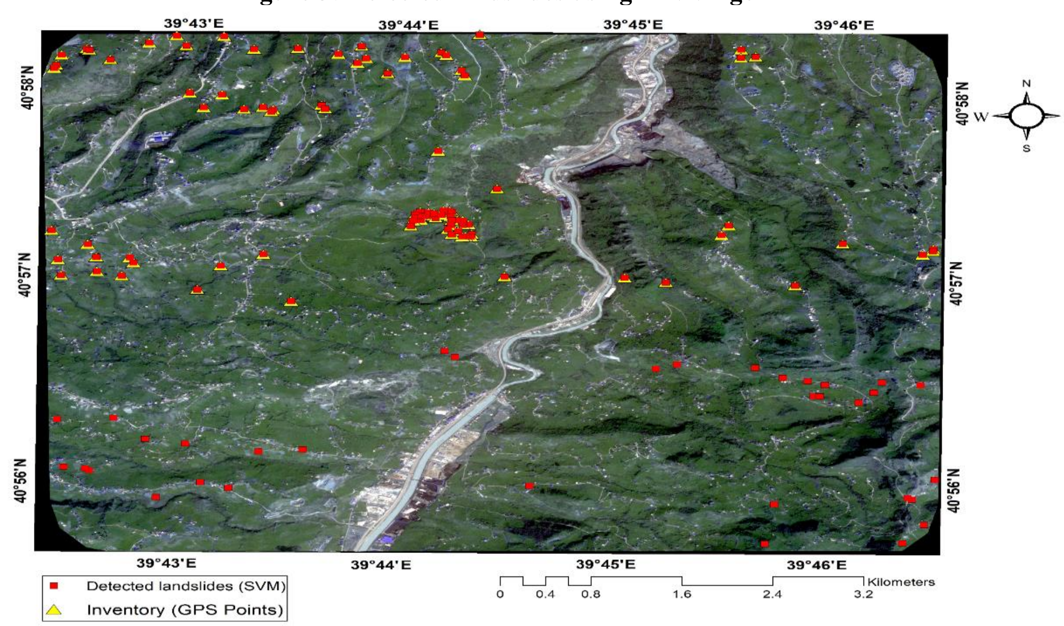

Figure 4: Detected landslides using SVM algorithm

The performance of different classifiers on imbalanced datasets

As presented in Table 3, SVM produced better results compared to k-NN algorithm. In the results of SVM algorithm, the lowest dataset (dat2) was 83.75% and the highest (dat5) was 85.12%. Thus, the accuracy results of SVM classifier were not significantly different among the five different training sample sizes.

On the other hand, the classification accuracy of k-NN was significantly different between the smallest sample size (dat1, 79.80%) and the largest sample size (dat5, 84.59%). There is a difference between classification accuracies of SVM and k-NN because of the small and imbalanced training samples (dat1, dat2 and dat3). Compared to k-NN, SVM produced a significantly higher accuracy. This position agree with the results in Shi and Yang (2015). As the sample size increased from dat1 to dat5, there was a significant increase in the accuracy of k-NN, while the results of SVM only showed slight increment. These show that the effects of the sample size and imbalanced data of training samples are more pronounced on the classification accuracy for k-NN than for SVM.

The highest accuracy for the k-NN (84.59%) and SVM (85.12%) classifiers were recorded at the largest training sample size (dat5). But with the smaller training sample sizes, the overall accuracy of the classifiers were on the decrease. A study by Noi and Kappas (2018) suggests that large amount of data is required to produce the best performance of classifiers in the situation where the training sample data is imbalanced between classes. However, too large sample size can alter the proportion between classes and decrease the overall accuracy. It is important to note that the highest accuracies in k-NN and SVM classifiers were obtained when the training sample size represented about 0.26% of the total study area. This agrees with the study reported in Colditz (2015) using Random Forest classifier.

Table 3: Accuracy of k-NN and SVM classifiers on different imbalanced training sample sizes

Classifiers and Sub-datasets	k-NN dat1	k-NN dat2	k-NN dat3	k-NN dat4	k-NN dat5	SVM dat1	SVM dat2	SVM dat3	SVM dat4	SVM dat5
Overall Accuracy (%)	79.80	82.06	82.60	83.37	84.59	83.95	83.75	84.33	84.78	85.12

The performance of different classifiers on balanced datasets

The SVM algorithm still produced a better accuracy (85.07%) compared to k-NN classifier (84.10%) when balanced datasets was used (Table 4). However, there was no pronounced difference on the performance of the two classifiers on different training sample sizes. The effect of the training sample size was strong on the accuracy of k-NN classifier when small training sample size (dat1 to dat 4) was used. The overall pattern in the accuracy of k-NN algorithm shows that higher accuracy was obtained with larger training sample size. When the sample size was increased from 40% (dat4) to 50% (dat5), the accuracy also increased from 83.45% to 84.10%.

The accuracy of SVM algorithm shows a different pattern of results. When using small size training sample (dat1 and dat2), the accuracy of SVM classifier was high and changed slightly at 82.73% and 82.45%, respectively. But the increase of the training sample size from dat3 (30%) and dat4 (40%) created a strong effect on SVM classification accuracy. The two classifiers produced the highest accuracy when the balanced training sample size increased from 0.20% (dat3) to 0.32% (dat5) of the total study area. The results agree with previous study reported in Shao and Lunetta (2012).

Table 4: Accuracy of k-NN and SVM classifiers on different balanced training sample sizes

Classifiers and Sub-datasets	k-NN dat1	k-NN dat2	k-NN dat3	k-NN dat4	k-NN dat5	SVM dat1	SVM dat2	SVM dat3	SVM dat4	SVM dat5
Overall Accuracy (%)	79.85	80.50	81.81	83.45	84.10	82.73	82.45	83.71	84.95	85.07

Conclusion

The paper attempted to compare and evaluate the performance of two supervised classifiers (k-NN and SVM) for detection and mapping of slow-moving landslides using Pleiades-1 data. The adopted approaches combined object-based image analysis with k-NN and SVM supervised learning algorithms, and were able to detect 95% of the number of slow-moving landslides present in the study area, using VHR Pleiades-1 image. A total of 128 small landslides were detected in the study area using k-NN algorithm, while a total of 134 landslides were detected using SVM algorithm. The SVM method had higher producer accuracy (85.9%), user accuracy (89.4%) and kappa index (0.82) compared to the k-NN algorithm that had producer accuracy (83.1%), user accuracy (86.0%) and kappa index (0.80). The results obtained in this study have added to the growing number of applications of object-based image analysis (OBIA) for semi-automated landslide mapping using VHR optical data.

The performances of the two classifiers on imbalanced and balanced datasets were also presented. There was no significant difference between the performance of k-NN and SVM on balanced and imbalanced datasets when training sample sizes were large. This implies that when the training samples were large enough, the classifiers were less sensitive to the imbalanced training data. It was shown that the performance of the k-NN classifier was less sensitive with imbalanced training sample data, and varied with training sample sizes. For the SVM classifier, the results of imbalanced and balanced were similar and very high (greater than 85.0%), when the training sample sizes were large enough. In all, the SVM classifier produced better overall accuracies for both imbalanced and balanced sub-datasets, compared to the performance of the k-NN classifier.

The overall evaluations of the two classifiers show that using supervised classification at object level with Pleiades-1 image, for slow-moving landslide detection and mapping, is possible and can be improved. The results of this study show that both k-NN and SVM are suitable classifiers for object classification using Pleiades-1 data, with SVM producing better results compared to k-NN classifier.

References

Akbulut, Y., Sengur, A., Guo, Y. & Smarandache, F. (2017). NS-k-NN: Neutrosophic Set-Based k-Nearest Neighbors classifier. *Symmetry*, 9, 1-10.

Archibald, R. & Fann, G. (2007). Feature selection and classification of hyperspectral images with support vector machines. *IEEE Geoscience and Remote Sensing Letters*, 4, 674-677.

Ballabio, C. & Sterlacchini, S. (2012). Support vector machines for landslide susceptibility mapping: The Staffora River Basin case study, Italy. *Math Geosci*., 44, 47-70.

Cheng, G., Guo, L., Zhao, T., Han, J., Li, H. & Fang, J. (2013). Automatic landslide detection from remote-sensing imagery using a scene classification method based on BoVW and pLSA. *Int. J. Remote Sensing*, 34, 45-59.

Colditz, R. R. (2015). An evaluation of different training sample allocation schemes for discrete and continuous land cover classification using decision tree-based algorithms. *Remote Sensing*, 7, 9655-9681.

Cruden, D. M. & Varnes, D. J. (1996). Landslide types and processes. In: Turner, A.K., Schuster, R.L. (eds.) *Landslides, Investigation and Mitigation*, Special Report 247. Transportation Research Board, Washington D.C., pp 36-75.

de Vries, M. V. W., Arrell, K., Basyal, G. K., Densmore, A. L., Dunant, A. L., Harvey, E. L., Jimee, G. K., Kincey, M. E., Li, S., Pujara, D. S., Shrestha, R., Rosser, N. J. & Dadson, S. J. (2024). Detection of slow-moving landslides through automated monitoring of surface deformation using Sentinel-2 satellite imagery. *Earth Surface Processes and Landforms*, 49(4), 1397-1410

Franco-Lopez, H., Ek, A. R. & Bauer, M. E. (2001). Estimation and mapping of forest stand density, volume and cover type using the k-Nearest Neighbors method. *Remote Sens. Environ*., 77, 251-274.

Fu, S., de Jong, S. M., Nijland, W., Gravey, M., Kraaijenbrink, P. & de Haas, T. (2025). Retrieving 4D landslide displacement using Pléiades satellite stereo pairs on the La Valette landslide. *International Journal of Applied Earth Observation & Geoinformation*, 140, 1-15.

Guzzetti, F., Mondini, A. C., Cardinali, M., Fiorucci, F., Santangelo, M. & Chang, K.-T. (2012). Landslide inventory maps: New tools for an old problem. *Earth Sci. Review*, 112, 42-66.

He, H. & Garcia, E. A. (2009). Learning from imbalanced data. *IEEE Transactions on Knowledge & Data Engineering*, 21(9), 1263-1284.

Heleno, S., Matias, M., Pina, P. & Sousa, A. J. (2016). Semi-automated object-based classification of rain-induced landslides with VHR multispectral images on Madeira Island. *Nat. Hazards Earth Syst. Sci*., 16, 1035-1048.

Hölbling, D., Füreder, P., Antolini, F., Cigna, F., Casagli, N. & Lang, S. (2012). A semi-automated object-based approach for landslide detection validated by persistent scatterer interferometry measures and landslide inventories. *Remote Sensing*, 4 (5), 1310-1336.

Kavzoglu, T., Sahin, E. K. & Colkesen, I. (2015). Selecting optimal conditioning factors in shallow translational landslide susceptibility mapping using genetic algorithm. *Engineering Geology*, 192, 101-112.

Lee, S., Hong, S.-M. & Jung, H.-S. (2017) A Support Vector Machine for landslide susceptibility mapping in Gangwon Province, Korea. *Sustainability*, 9(1), 1-15.

Li, Y., Chen, G., Wang, B., Zheng, L., Zhang, Y. & Tang, C. (2013). A new approach of combining aerial photography with satellite imagery for landslide detection. *Nat. Hazards*, 66, 649-669.

Mountrakis, G., Im, J. & Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry & Remote Sensing*, 66, 247-259.

Noi, P. T. & Kappas, M. (2018). Comparison of Random Forest, k-Nearest Neighbor, and Support Vector Machine classifiers for land cover classification using Sentinel-2 imagery. *Sensors*, 18, 1-20.

Novellino, A., Pennington, C., Leeming, K., Taylor, S., Alvarez, I. G., McAllister, E., Arnhardt, C. & Winson, A. (2024). Mapping landslides from space: A review. *Landslides*, 21, 1041-1051

Qian, Y., Zhou, W., Yan, J., Li, W. & Han, L. (2015). Comparing machine learning classifiers for object-based land cover classification using very high resolution imagery. *Remote Sensing*, 7, 153-168.

Rana, D., Dadkhah, H., Ghaderpour, E., Bozzano, F. & Mazzanti, P. (2026). Monitoring slow-moving landslides through PS-InSAR and antecedent precipitation index: a case study of Petacciato, Italy. *International Journal of Remote Sensing*, 47(6), 2605-2634.

Sassa, K., Tsuchiya, S., Fukuoka, H., Mikos, M. & Doan, L. (2015). Landslides: Review of achievements in the second 5-year period (2009–2013). *Landslides*, 12, 213-223.

Shao, Y. & Lunetta, R. S. (2012). Comparison of support vector machine, neural network, and CART algorithms for the land-cover classification using limited training data points. *ISPRS J. Photogramm. Remote Sensing*, 70, 78-87.

Shi, D. & Yang, X. (2015). Support vector machines for land cover mapping from remote sensor imagery. In: *Monitoring and Modeling of Global Changes: A Geomatics Perspective*. Springer: Dordrecht, The Netherlands, 2015; pp. 265-279.

Statnikov, A., Wang, L. & Aliferis, C. F. (2008). A comprehensive comparison of random forests and support vector machine for microarray-based cancer classification. *BMC Bioinformatics*, 9, 1-10.

Stumpf, A. & Kerle, N. (2011). Object-oriented mapping of landslides using random forests. *Remote Sensing of Environment*, 115, 2564-2577.

Vapnik, V. (1999). *The nature of statistical learning theory*. Springer-Verlag

Yalçinkaya, M. & Bayrak, T. (2005). Comparison of static, kinematic and dynamic geodetic deformation models for Kutlugün landslide in North-eastern Turkey. *Natural Hazards*, 34, 91-110.